Efficiency Outcomes of Market Concentration and Managed Care

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Abstract

The paper examines how hospital cost efficiency has reacted to extensive horizontal integrations of hospitals and rapid growth of managed care in the US health care industry. Cost efficiency is estimated by using panel data approaches to relax the assumptions for the hospital effects imposed in earlier studies. The paper shows that higher managed care penetration over time is associated with greater hospital efficiency, and higher market concentration is positively associated with efficiency when markets are highly competitive or highly concentrated.

JEL Classification: C23; I11; L41

Keywords: Competition; Cost Efficiency; Managed Care; Panel Data; Stochastic Frontier Function

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1 Introduction

Health care expenditures are substantially higher in the United States than in any other industrialized country. The share of health care expenditures in GDP more than doubled from 1960 to 1990. It reached 13 percent in 1999 and is expected to reach 15.5 percent in 2008 (Health Care Financing Administration 2001). The growth in total health care spending is associated with an overall increase in health care costs from all sources, including hospital costs, which grew by 7.6 percent per year in the period of 1980-1998. The rate of growth was even higher in government programs: nine percent in Medicare program and 10.2 percent in Medicaid. The total costs of these health care programs grew even faster in Florida than the rest of the country. For the same period, hospital costs in Medicare and Medicaid programs increased by 1.1 and 3.6 percent more in Florida than the national average, respectively (Health Care Financing Administration 2001).

In an effort to control rapidly rising health care costs, not only employers but also the state and federal governments have chosen managed care plans to provide health care for their beneficiaries. Medicare enrollment in health maintenance organizations (HMOs) has increased rapidly during the last decade. Consequently, the overall enrollment in HMO plans increased from 37.6 million in 1992 to 80.4 million in 2000 (InterStudy 2001).

Managed care organizations (MCOs) intervene in treatment decisions by limiting type of treatments or providers from whom treatment can be obtained. The plans set up a predetermined, selectively contracted network of providers and bargain for lower rates to join the network (Glied 2000). It is accepted that this feature of managed care is an effective tool in controlling health care costs. However, it is not clear whether cost saving is achieved at the expense of quality. A decrease in health care costs may come from different sources: it may be due to a reduction in quality for the same hospital product or an improvement in efficiency as providers allocate resources more efficiently, or a combination of both. This empirical question on cost efficiency is one of the focuses of this paper.

In addition to a rapid increase in managed care penetration, extensive horizontal consolidations in hospital markets have also been an important feature of the US health care industry during the last decade (for an extensive review see Gaynor and Haas-Wilson 1999). Within two years, from 1994 to 1996, more than 40 percent of all hospitals were involved in mergers, acquisitions, joint ventures or partnerships. There were more than 200 hospital mergers in 1997 alone (Haas-Wilson and Gaynor 1998). This recent dynamic in hospital markets has raised questions about the anti-competitive behavior of hospitals in the form of raising prices and gaining bargaining power relative to insurers and self-insured firms. The net impact of mergers on social welfare, however, is not obvious, since horizontal consolidations can have both anti-competitive and pro-competitive impacts. As firms increase in size, likelihood of exercising market power increases. Mergers are one means of maintaining excess firm capacity and committing to price aggressively to deter entry (Spence 1977). On the contrary, horizontal integrations may promote cost efficiency by decreasing excess capacity in the industry (Connor et al. 1997).

The purpose of the paper is to measure hospital cost efficiency by using panel data from the State of Florida and to test impacts of market concentration and managed care penetration on cost efficiency. In this paper, I apply both the stochastic frontier and the panel data approaches to quantify the cost efficiency. Only a few studies have applied the stochastic frontier approach to US hospital markets. The results of these studies are contingent on the validity of the assumptions that inefficiency is a constant random variable, and is drawn from a specific distribution (Frech and Mobley 2000; Zuckerman, Hadley, and Iezzoni 1994). Panel data techniques, however, provide alternative definitions for estimation of inefficiency, which does not require these assumptions. In order to assess robustness of inefficiency measures to these assumptions, the panel data models developed in Schmidt and Sickles (1984) and Cornwell, Schmidt and Sickles (1990) are used in this paper.

The plan of the paper is as follows. Section 2 provides a background and a brief review of earlier studies on stochastic frontier estimations. Section 3 presents the sample, data sources, the specification for the cost function and variable definitions. Empirical issues, including hospital inefficiency measures under different assumptions, are discussed in the fourth section. In section 5, I discuss the empirical analysis for hospital inefficiency and estimate a hospital inefficiency model to evaluate the impacts of managed care penetration and hospital competition on efficiency. Section 6 presents the results from the regression analysis. The last section is devoted to conclusions.

2 Background and Literature Review

Several approaches for the measurement of inefficiency in production and cost have been developed since Farrell (1957). In his pioneering study, Farrell provides definitions and a computational framework for both technical and allocative efficiency. In determining a firm-specific inefficiency, one of the estimation techniques is the Data Envelopment Analysis (DEA), which is applied in several studies to determine inefficiency in different industries, such as banking and telecommunication. The basic idea behind this approach is to search for an optimal combination by using observed combinations of inputs and outputs. It ignores the possibility of random fluctuations in any data set and assumes that an observed production process would be efficient. In fact, there are two types of factors affecting performances of the firms: some can be entirely external factors, out of the firms' control such as luck, climate, and poor machine performance; and others can be entirely controlled by the firms. Consequently, not all deviations from the frontier, but only those controlled by the firms would be attributed to inefficiency [1].

The stochastic frontier approach developed in Aigner, Lovell, and Schmidt (1977) is an alternative approach, which relaxes the assumptions imposed by the DEA. The main argument in the stochastic frontier approach is that deviations from the frontier may not always be managed by the firm. For instance, a study that uses the DEA in health care industry would include the unobserved random fluctuations of patient mix in inefficiency, but they would be considered as a part of the random error in the frontier approach.

The frontier approach depends on two-component error terms in cost function: one normal and the other from a one-sided distribution. Under the distributional assumption for the error terms, the total cost function for hospital i can be defined as

$$C_i = C(Q_i, W_i, Z_i)e^{(u_i + v_i)} \tag{1}$$

where v_i is a normally distributed random error with zero mean and variance σ_v^2, and Q_i, W_i and Z_i stand for output measures, input prices and output descriptors for hospital i.

The inefficiency term, u_i is assumed to be positive and is distributed so that its absolute value is normal with zero mean and variance σ_u^2. The positive disturbance reflects the fact that each firm's cost must lie on or above its cost frontier. This implies that any deviation from the frontier is caused by the factors controlled by the firms.

[1] For a review of both the deterministic and stochastic frontier approaches, see Forsund, Lovell and Schmidt (1980)

Following Aigner, Lovell, and Schmidt (1977), only a few studies have applied the stochastic frontier cost approach to health care markets. Frech and Mobley (2000) study hospital markets in order to identify the effect of differences in inefficiency on growth and market concentration. Similarly, Zuckerman, Hadley and Iezzoni (1994) investigate efficiency outcomes of profit motives, market forces and other hospital characteristics. Vitaliano and Toren (1994) apply the same approach to estimate inefficiency in nursing homes.

The studies mentioned above apply the frontier model to cross-sectional data, which has two drawbacks. First, it requires a strong assumption for the inefficiency term to ensure separation of inefficiency from random noise. Second, it creates a bias in efficiency estimations if some variables, such as unobservable input and output quality, are omitted. As a result, the parameters in the stochastic frontier are estimated inconsistently, which leads to biased estimates of inefficiency scores. The existence of hospital specific unobservable variables and imperfectly observable quality in hospital services support applications of panel data approaches in cost efficiency analysis. As suggested in Dor (1994), panel data estimators are preferable, because they are less likely to yield biased estimates of coefficients for variables in the stochastic frontier and they require fewer distributional assumptions about the deterministic error.

The panel data techniques have been used extensively in the production and cost estimations. However, Schmidt and Sickles (1984) is the first study that applies panel data techniques to the frontier framework. They introduce a model, which does not require any distributional assumption for inefficiency in isolating it from statistical noise. One of the disadvantages of their model is that the firm-specific inefficiency is assumed to be time invariant. As it is pointed out by several subsequent studies (Cornwell and Schmidt 1996; Cornwell, Schmidt, and Sickles 1990; Kumbhakar 1990), this assumption is too strong and unrealistic, especially in long panels. In later studies, this limitation is pointed out and new techniques are developed to relax the time-invariance assumption on inefficiency. These are discussed in a greater detail in the fourth section.

3 Data and Model Specification

3.1 Sample and Data Sources

The sample includes 876 observations, an average of 125 short-term general and specialty hospitals per year over a 7-year period from Florida [2]. The main database is the American Hospital Association (AHA) Annual Hospital Survey, which contains variables about admissions, cost measures, staffing, and other hospital level variables, such as ownership status, bed size, location, and teaching status. Since the AHA provides information for all hospitals, including name and zip codes of every hospital, the market concentration index – the Herfindahl-Hirschman Index (HHI) - is calculated using this database. The relevant market area is assumed to be counties. Additionally, the proportions of Medicare and Medicaid discharges and surgical operations are obtained from the AHA database.

Output measures, such as average age of admitted patients, average number of secondary diagnosis, and complication rates are calculated using the Nationwide Inpatient Sample (NIS) from the Agency for Health Care Research and Quality (AHRQ). The NIS is currently the largest available inpatient care database, which contains data from approximately 6.5 million hospital

[2] The data set covers all years from 1990 to 1997, except 1993. Since the AHA database has inconsistent information on surgical operations and hospital costs, the data from 1993 are excluded.

stays taken annually from about 850 hospitals. It also includes more than 100 clinical and non-clinical variables for each hospital stay.

In addition to the NIS and AHA databases, the Area Resource File (ARF), and the Health Care Financing Administration (HCFA) Case-mix index file are also used. The ARF has information on demographic, economic, and health factors at the county level. The HCFA Case-mix index file, on the other hand, provides a measure of the costliness of cases treated by a hospital relative to the national average cost of all Medicare hospital cases, using Diagnosis Related Group (DRG) weights as a measure of relative costliness of cases.

3.2 Specification for the Cost Function

Following Frech and Mobley (2000), the hospital cost frontier function is estimated in the form of a first-order logarithmic approximation as [3]

$$log\, C_{it} = \alpha + \beta_1\, log\, Q_{it} + \beta_2\, log\, W_{it} + \beta_3\, log\, Z_{it} + \varepsilon_{it} \qquad (2)$$

where C_{it} is the total expenditures, Q_{it} stands for the output measures, W_{it} denotes the input prices and Z_{it} is the output descriptors for hospital i at time t. Errors are composed of two terms: statistical noise and measures of inefficiency for each hospital relative to the most efficient hospital.

Table 1 reports definitions and descriptive statistics for all variables used in the analysis. The main independent variables are the output and output characteristics. I measure the hospital output in volume, therefore, instead of using patient days, I use admissions and outpatient visits as the hospital outputs. Unlike length of stay or patient days, number of individuals treated is

[3] Hospital efficiency is also estimated by defining a cost function in translog form. The results are insensitive to the specification in the cost function.

exogenous: patient days are affected by the treatment decision of a hospital, whereas the flow of patients is not directly determined by the hospital. (Breyer 1987; Frech and Mobley 2000; Zuckerman, Hadley, and Iezzoni 1994).

Other dimensions of outputs are also included in the cost function estimation. It is likely that Medicare and Medicaid patients differ from the general population in terms of the average severity of illnesses. The percentage of Medicare and Medicaid discharges are included to account for this possibility. The proportions of inpatient and outpatient surgeries in total admissions and in total outpatient visits are also included to capture the service intensity differences.

In addition to output and input prices, other factors would also affect the shape of the cost function. In order to capture the heterogeneous nature of hospital products, I include the average patient and the hospital characteristics: some hospitals may experience a high rate of cost due to admitting severely ill patients or providing higher quality in their services. If these factors are not controlled, measured inefficiency scores will have an upward bias for high quality hospitals. As a solution, observed demographic differences in patient mix, such as average patient age, percentage of patients who are older than 64 and younger than one year old, and the proportions of female patients, are added to the model. In addition, the case mix index of each hospital, the proportion of patients who experience adverse and iatrogenic complications and wound infections, and the average number of secondary diagnosis are also used to control for heterogeneity in patient mix and product quality (Dranove and Ludwick 1999; Sari 2002).

4 Empirical Framework

This section presents estimation procedures for both the hospital cost function, and hospital inefficiency. After the parameters are obtained from the cost function estimation, it is possible to calculate the inefficiency scores for each hospital. Inefficiency for hospital *i* at time *t*, measured as a percentage deviation from the most efficient cost structure, is defined as

$$Inefficiency_{it} = 1 - e^{-u_i} \tag{3}$$

Hospital inefficiency is used both in the technical and allocative sense. Technical efficiency is defined either as producing the maximum output for a given level of inputs, or using the minimum inputs to produce a certain level of output. Allocative efficiency, however, measures deviations from the cost-effective allocation of resources in production. A firm is assumed to be allocatively inefficient if the marginal rate of substitution between any two inputs is not equal to the corresponding input price ratio.

4.1 Hospital Inefficiency Estimations based on the Stochastic Frontier Approach

The cost function is estimated, using an algorithm developed by Aigner, Lovell, and Schmidt (1977). The algorithm estimates a maximum likelihood estimator, using the OLS results as starting values. Once the function converges, the inefficiency scores for each hospital can be calculated by using the procedure defined in Jondrow et al. (1982). This procedure, however, is based on a cross-section data set [4]. In order to utilize panel data, the stochastic cost function is estimated by applying a random effect approach. Similar to the technique based on cross-

[4] If the frontier function is defined in terms of original values, this calculation does not require any corrections. However, in the logarithmic specification $E[exp(-u_i)| u_i + v_i]$ rather than $E[u_i \mid u_i + v_i]$ should be used.

sectional data, the new algorithm applied in this paper uses OLS estimates as starting values. In the next step, it calculates the maximum likelihood estimates as an intermediate step under the assumption that the sample is cross-sectional. At the final stage, it calculates the maximum likelihood estimators from panel data. These estimators are presented in Model 1 of Appendix Table A1.

In estimating the inefficiency scores, Battese and Coelli (1988) develop a method based on panel data models that is a generalization of Jondrow et al. (1982). Under the time invariant inefficiency assumption, the residuals from the stochastic cost function are used to calculate the inefficiency scores. In this procedure, the inefficiency term is assumed to be a half-normal random variable. To calculate the inefficiency scores from expression (3), the conditional expectation is calculated as (Battese and Coelli 1988; Greene 1991):

$$E[e^{-u_i}|\varepsilon_{it}] = \{\frac{1-\Phi[\sigma_* - (\mu_i^* / \sigma_*)]}{1-\Phi(-\mu_i^* / \sigma_*)}\} e^{(-\mu_i^* + 0.5\sigma_*^2)} \quad (4)$$

In this expression, Φ stands for the cumulative normal distribution and μ_i^* and σ_*^2 are expressed as

$$\mu_i^* = -\sigma^2 \bar{\varepsilon}_i / \sigma^2 + T_i^{-1}\sigma_v^2 \text{ and } \sigma_*^2 = \sigma^2\sigma_v^2(\sigma_v^2 + T_i\sigma^2)^{-1}$$

where σ^2 and σ_v^2 are the variances of ε_{it} and v_{it}, T_i stands for the number of years hospital i observed in the sample, and $\bar{\varepsilon}_i$ denotes the mean of ε_{it} over time.

After substituting the conditional expectation from expression (4) for the exponential of minus u_i in expression (3), hospital inefficiency is calculated and is denoted by *Inefficiency-1* in Table 2.

4.2 Alternative Inefficiency Estimations

The calculation of *Inefficiency-1,* described above, requires time invariance for hospital efficiency and specific distributional assumptions for the inefficiency term. In this section, alternative methods for inefficiency estimations are discussed in order to relax these assumptions. While the first approach summarized in section 4.2.1 is a method to relax the distributional assumptions for the inefficiency term, the approach discussed in section 4.2.2 relaxes both the distributional and time invariance assumptions. These methods require the estimation of the cost function with panel data approaches. Therefore, the cost function is estimated with panel data approach and the parameter estimates are presented in the Model 2 of the Appendix Table A1.

4.2.1 Time invariant inefficiency

The time invariant approach, which relaxes the distributional assumption for the inefficiency term, was developed by Schmidt and Sickles (1984). Following Schmidt and Sickles, it is convenient to rewrite the model in equation (2) as

$$log\, C_{it} = \alpha_i + X'_{it}\beta + v_{it} \tag{5}$$

where $\alpha_i = \alpha + u_i$, and X_{it} is a matrix of all independent variables.

After obtaining estimates for β by using the random effect panel data approach, it is easy to recover the estimates of the firm intercepts. Let us define the residuals from the cost function as $e_{it} = \log C_{it} - X_{it}'\hat{\beta}$. Then the firm intercepts, α_i can be estimated as an average of the residuals as

$$\hat{\alpha}_i = \frac{1}{T_i}\sum_t e_{it} \tag{6}$$

Without loss of generality, we can normalize inefficiency for the least inefficient hospital to zero. Under this normalization, one can estimate u_i for each hospital i as

$$u_i = \hat{\alpha}_i - \min_i(\hat{\alpha}_i) \tag{7}$$

After obtaining u_i for all hospitals from equation (7), the inefficiency scores for each hospital are calculated using equation (3). This is based on the assumption that one or few hospitals with minimum hospital effects are 100 percent efficient relative to all others. These inefficiency scores are labeled *Inefficiency-2* in Table 2.

4.2.2 Time variant inefficiency

The time invariant inefficiency assumption is very restrictive given the fact that health care industry experiences substantial changes. Cornwell, Schmidt and Sickles (1990) and Bauer (1990) developed new methods to relax this assumption. It is assumed that the hospital effects have two components: $\alpha_{it} = \alpha_t + u_{it}$. The first term is the common frontier intercept at time *t,* and the second term is the time variant inefficiency term. Furthermore, the hospital effects are defined as a function of time with parameters vary over hospitals:

$$\alpha_{\text{it}} = \sum_{j=0}^{J}\theta_{i(j+1)}t^j \tag{8}$$

In expression (8), the choice of J determines the number of parameters estimated for each hospital. While it provides a flexible form for the hospital effects, a larger value for J significantly decreases the degrees of freedom. Following Cornwell, Schmidt and Sickles (1990) and Bauer (1990), a quadratic form is used in the expression above. Since the residuals are the estimates of $(\alpha_{it} + v_{it})$, one can regress residuals for hospital i on time and time squared to estimate parameters in expression (8) for each hospital [5].

Once the hospital effects are estimated, one can calculate the inefficiency terms as a difference between the estimated hospital effect for hospital i at time t, and the frontier intercept at time t. For each year, the least inefficient hospital is determined and assumed to be 100 percent efficient. Then the inefficiency scores are calculated for all other hospitals by taking the least inefficient hospital as the reference point (see Atkinson and Cornwell (1994 ; 1998) for applications in airline industry). Therefore u_{it} is defined as

$$u_{it} = \hat{\alpha}_{it} - \min_{t} \hat{\alpha}_{it} \tag{9}$$

where the second term is the frontier intercept at time t.

Using equation (3), the inefficiency scores labeled *Inefficiency-3* in Table 2 are calculated using the method described above.

4.2.3 Sensitivity Analysis

The approaches, developed in Schmidt and Sickles (1984), and Cornwell, Schmidt and Sickles (1990), impose fewer assumptions on the inefficiency terms; therefore, provide flexible estimation techniques for hospital inefficiency. However, the major disadvantage is the

[5] The fitted values from each regression provide an estimate of the time variant hospital effects, α_{it} that is consistent (for all i and t) as T goes to infinity (Cornwell, Schmidt, and Sickles 1990). The same condition is also required for consistency in the model proposed by Schmidt and Sickles and in the stochastic frontier approach. I follow Battese and Coelli (1988) who use a 3-year panel data set to apply the stochastic frontier approach to the Australian dairy industry. Therefore, I include hospitals, which are observed at least for 3 years in a 7-year panel data set. This choice is determined by the availability of the data. 3-7 years may generally not be viewed as approximately infinite.

sensitivity of inefficiency scores to outliers, especially when an outlier is chosen as a reference point. Using the method of Hadi (1992; 1994), I test the existence of outliers in the sample. This diagnostic test identifies outliers only at the upper end but not at the lower end. Since the outlier hospitals are not identified as benchmarks, the inefficiency estimates for other hospitals are not affected [6].

Furthermore, I examine the sensitivity of inefficiency estimates to the specification of the cost function. First, I include net payroll benefits in the cost function as an additional input price variable. The correlation coefficient between the original and new inefficiency estimates are 0.97 for both *Inefficiency-2* and *Inefficiency-3* measures. Second, to control for output heterogeneity that leads to overestimation of hospital inefficiency, I include both patient level variables and the HCFA case mix index of each hospital. To evaluate the power of the HCFA case mix index variable on inefficiency, I estimate the inefficiency scores without the HCFA case mix index variable in the frontier function. In this case, mean inefficiency increases by 3 to 4 percentage points. The correlation coefficient also decreases to 0.95, suggesting that the HCFA case mix index variable has a significant power in explaining the case mix differences among hospitals. Therefore ignoring severity controls, such as the HCFA case mix index variable, creates misleading conclusions. Third, I include days of stay as a right hand side variables in the cost functions and estimate hospital inefficiency. The results presented in the paper are robust to the specification in the cost function.

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[6] The summary statistics for *Inefficiency-3* in Table 2 and the regression results in Table 4 are not very sensitive to these observations. I apply the same test to *Inefficiency-2*. The mean inefficiency drops by 1 percent when the three outlier hospitals are removed.

In order to examine the power of the panel data applications in inefficiency measures, I compare results of cross sectional case to the panel data models. To do this, I estimate hospital inefficiency using cross sectional stochastic frontier approach and impose the constant inefficiency assumption using equation (4). For this purpose, I use the stochastic cost frontier routine in LIMDEP version 6.0 for each year separately and for the entire sample. Then I estimate *Inefficiency-2* and *Inefficiency-3* using a fixed effect in the cost functions. The correlations between the panel data inefficiency measures and the cross sectional models are significantly low; suggesting that the use of the panel data models in the estimation of inefficiency is reasonable.

5 Empirical Analysis of Hospital Inefficiency

The impact of market forces on the behavior of hospitals is examined by using the following form of the inefficiency model:

$$Inefficiency_{it} = f(HHI_{mt}, HMO_{mt}, Y) + \xi_{it} \tag{10}$$

where HHI_{mt} measures the competition in market *m* at time *t*, and HMO_{mt} is the market level managed care penetration at time *t*. *Y* stands for all other variables including hospital characteristics.

In order to identify the impact of competition on the level of efficiency, the county level *HHI* is used as a measure of competition. The impact of managed care penetration on efficiency is captured using the county level HMO penetration as a regressor. Since, it is likely that inefficiency is different in highly concentrated markets and in markets with high-managed care penetration, higher order terms are also included in the empirical analysis.

Earlier studies claim that profit motives create incentives for cost efficiency; for instance, Frech (1976) argues that non-profit firms invest more in non-pecuniary benefits compared to profit firms. In order to identify the impact of ownership status on efficiency, dummy variables for public and non-profit hospitals are included in the regressions.

As a first step, I estimate the inefficiency model in equation (10), using ordinary least squares (OLS). Each column of Table 3 presents the parameter estimates in equation (10) for each inefficiency measures. The coefficients of market competition and ownership variables are significant and have the same sign in all models. Managed care penetration, however, is statistically insignificant in all models.

Some researchers have been skeptical about inefficiency estimations since unmeasured quality may create bias in inefficiency measures (Frech and Mobley 2000). If this is the case, the estimated impact of market concentration on inefficiency will be biased. In other words, if the unobserved output quality is not isolated from hospital inefficiency, observed correlation between market concentration and inefficiency will be because of the negative association between market concentration and high quality (Kessler and McClellan 2000; Sari 2002). It is also likely that in some instances there may be unobserved inherited input quality (e.g., with more experienced doctors and nurses in some hospitals) that may create bias in inefficiency calculations. To prevent such bias, one approach would be to apply panel data techniques in the inefficiency model of equation (10) by assuming that these factors are constant over time. This approach is applied for the time variant inefficiency measure - *Inefficiency-3*. An additional solution would be to include other regressors. For this purpose, adverse and iatrogenic complications and wound infections are included in both OLS and panel data models.

The parameters of equation (10) are estimated by both fixed and random effect models, using *Inefficiency-3* as a dependent variable. These results from panel data estimations are presented in Table 4. Random effects require that the regressors and hospital constant terms are independent. By construction, this assumption does not hold since a correlation between market concentration and unobserved quality is already assumed. I also test the independence assumption, using the specification test as described in Hausman (1978). The test statistic provides a strong evidence against the random effect assumption (p-value is less than 0.001). Hence, I use a fixed effect model, in which I experiment with higher order terms of managed care penetration and market concentration and report the results if they are statistically significant.

6 Results

Table 2 includes summary statistics and a correlation matrix for the three different inefficiency measures. The top panel of Table 2 presents the sample statistics and the bottom panel illustrates the Pearson correlation among the three inefficiency measures. The estimates of hospital level inefficiency are quite similar to the findings of earlier studies, which apply the frontier cost function approach using cross sectional data on hospitals in California. For instance, the overall inefficiency is 18.8 percent of total cost in Zuckerman, Hadley and Iezzoni (1994) and 20 percent of total cost in Frech and Mobley (2000). The inefficiency estimates of the current research from the stochastic approach provide similar results. The mean hospital inefficiency is 19.5 percent of total cost in the random effect frontier approach (see *Inefficiency-1* in Table 2). The range goes from zero or near zero for the most efficient hospital to 76 percent for the least efficient hospital. Average inefficiency rises as time invariance and distributional assumption for the hospital effects are relaxed. For instance, the mean is the highest (38 percent of hospital costs) for the least restrictive model (*Inefficiency-3*).

The Pearson correlation matrix is also presented to evaluate the rankings of hospital inefficiencies from different techniques. The correlation changes between 0.78 and 0.95. The correlation between the inefficiency measures calculated under the time invariant inefficiency assumption is quite high, suggesting that the hospital inefficiency rankings are robust to distributional assumption for the hospital effects. Once the invariance assumption is relaxed, the correlation decreases more than 13 percentage points.

Tables 3 and 4 report estimation results for the inefficiency model of equation (10), using OLS and panel data approaches. Although the coefficients for managed care penetration and ownership status are robust in all models, the estimate for market concentration is sensitive to the model specification. The direction of the relationship changes in the panel data estimations of Table 4. As described in the previous section, it is likely that unobserved input and output quality create bias in OLS coefficient estimates. For this reason, panel data techniques are applied to the time variant inefficiency measure (*Inefficiency-3*).

The results suggest that higher HMO market share is associated with lower hospital inefficiency. Although the coefficient estimate is insignificant in OLS results, the negative association between managed care penetration and inefficiency holds in all models. Other things being equal, the result from Model 4 in Table 4 implies that a 10-percentage point increase in HMO market share is associated with a 2.3 percentage point decrease in hospital inefficiency. Evaluated at the mean inefficiency of 38.1 percent, this corresponds to more than 6 percent decrease in hospital inefficiency.

After controlling for unobserved quality differences, the fixed effect results reveal that the association between cost inefficiency and market concentration changes depending on the level of competitiveness in the market. Marginal inefficiency with respect to market concentration, derived from the estimation results of model 4 in Table 4, is shown in Figure 1. It has an inverse U-shaped relationship, implying that there is an immediate efficiency gain as one moves away from a very competitive market. In order to check the sensitivity of the results to the model specification in the cost function, I estimate *Inefficiency-3* using a fixed effect in the cost function estimations. The impacts of market forces on efficiency are robust to the model specification in the cost function.

The result in terms of the impact of market competition on efficiency is consistent with the argument that horizontal integration may promote cost efficiency by decreasing excess capacity in health care markets (Connor et al. 1997). However, hospital mergers will not be effective in creating cost efficiency if the level of market competition is moderate. In other words, marginal inefficiency with respect to the *HHI* is positive if the *HHI* is between 0.26 and 0.71. This implies that inefficiency decreases with an increase in market concentration when the market concentration index is outside of this range.

7 Conclusions

The paper has examined impacts of managed care and market concentration on hospital efficiency. I use the three different models to estimate the hospital-specific inefficiency in Florida from the 7-year panel data set. The results suggest that the hospital inefficiency measures from different models are highly correlated, but the correlation decreases as one relaxes the time invariance assumption for the hospital effects.

In order to relax the restrictive assumptions of earlier studies, I use alternative models for estimating inefficiency. One of the crucial advantages of the last model implemented in this study *(Inefficiency-3)* is that one can estimate the hospital-specific inefficiency without using particular distributional structure and the time invariance assumption. This is important since it allows assessing the robustness of inefficiency measures to these assumptions. The results suggest that time invariance is a stronger assumption than distributional assumption for hospital inefficiency. This clearly makes sense in the long run, since the structure of health care provision and the market forces change substantially. Yet it matters here even with only 3 to 7 years in the sample. The other advantage of the time variant inefficiency measures is that one can control unmeasured factors, such as unobserved quality, in analyzing the impact of several factors on hospital efficiency.

The results provide evidences in favor of effectiveness of managed care in encouraging efficiency in health care markets. The results support that higher HMO market share is associated with higher hospital efficiency. Although there is evidence in this direction in all regression models, the positive association between the HMO market share and hospital efficiency becomes significant after controlling for unobserved quality differences among hospitals. The results imply that a 10-percentage point increase in HMO market share is associated with more than 6 percent decrease in hospital inefficiency. Using the total hospital costs of $419.5 billion in 1997 (Getzen 1997), this lowers the costs more than $2.5 billion per year.

After controlling for unobserved hospital quality, the results from the fixed effect reveal that hospital cost inefficiency has an inverse U-shaped association with rising market concentration. Inefficiency decreases until market concentration reaches a certain threshold, and starts to increase up to another threshold. This suggests that horizontal integration decreases inefficiency and saves money when the market does not have a moderate level of competition.

This paper is based on the assumption that the time invariance and distributional assumptions can be relaxed by using panel data. The consistency of parameter estimates in the cost function, and the inefficiency estimates requires a large sample over a longer period of time. Further research with longer panel data, therefore, would be useful in enhancing our understanding of hospital inefficiency and reevaluating the assumptions imposed in this literature.

Table 1: Means and Standard Deviations of Variables

Variables	*Definition of variables*	*Mean*	*Std. Dev.*
Cost	Log (total expenditures)	17.38	1.07
Admission	Log (total admissions)	8.50	1.02
Visit	Log (Outpatient admissions)	10.69	1.03
Wage	Log (total payroll expenses divided by the number of full-time equivalent employees)	10.23	0.22
Average Patient Characteristics:			
Adverse	Percentage of adverse/iatrogenic complications in total discharges	2.80	2.16
Wound	Percentage of wound infections in total discharges	0.28	0.19
Age	Average age of admitted patients	53.42	11.66
Baby	Percentage of infants (less than one year old)	8.20	8.30
Age65	Percentage of elderly (aged 65 and above)	46.30	17.35
Died	Percentage of patients died during the treatment	3.29	1.55
NDX	Average number of secondary diagnosis	4.43	1.13
Female	Percentage of female patients	56.90	5.17
Hospital Characteristics:			
Medicare	Percentage of Medicare discharges	45.16	14.62
Medicaid	Percentage of Medicaid discharges	12.12	8.81
Surgical outpatient	Percentage of outpatient surgical visit in total outpatient visits	5.20	4.44
Surgical inpatient	Percentage of inpatient surgery in total admissions	31.14	13.29
Log (size)	Log (total number of beds)	5.02	0.90
CMI	HCFA Case-mix index of each hospital	1.37	0.21
Urban	Urban hospitals	0.77	0.42
Teaching	Teaching hospitals	0.05	0.22
Public	Hospitals owned and operated by public parties	0.16	0.37
Non-profit	Non-profit private hospitals	0.47	0.50
County Level variables:			
Income per capita	Per capita income in thousand U.S dollars	20.58	5.73
Bed1000	Number of beds per 1000 population	4.74	4.19
Log (population)	Log (county population)	12.42	1.34
Unemployment	Unemployment rate	6.27	2.12
Emergency	Outpatient emergency admissions per 1000 population	384.65	132.10
HHI	Herfindahl-Hirschman index by county	0.37	0.30
HMO	HMO penetration by county	0.14	0.10

Table 2: Inefficiency Measures from Different Methods

A. Sample Statistics for different Inefficiency Measures

	Inefficiency-1	Inefficiency-2	Inefficiency-3
Mean	0.195	0.313	0.381
Standard deviation	0.114	0.120	0.133
Minimum	0.018	0.000	0.000
Maximum	0.635	0.676	0.757

B. Pearson Correlation Among different Inefficiency Measures

	Inefficiency-1	Inefficiency-2
Inefficiency-2	0.949	
Inefficiency-3	0.777	0.822

Note: Inefficiency-1: Time invariant inefficiency scores using the random effect stochastic cost function. Inefficiency-2: Time invariant inefficiency scores without distributional assumption for the hospital effects. Inefficiency-3: Time variant inefficiency scores without distributional assumption for the hospital effects.

Table 3: Regression Results for Different Inefficiency Measures

Dependent variable:	*Inefficiency-1*	*Inefficiency-2*	*Inefficiency-3*
HHI	-0.136	-0.119	-0.114
	(-2.74)	(-2.07)	(-1.90)
HHI^2	0.174	0.131	0.115
	(3.83)	(2.60)	(2.19)
HMO	-0.077	-0.064	-0.087
	(-0.92)	(-0.61)	(-0.85)
HMO^2	0.01	-0.071	-0.145
	(0.06)	(-0.31)	(-0.65)
Public	0.065	0.072	0.06
	(6.49)	(6.53)	(5.41)
Non-profit	0.086	0.088	0.078
	(10.97)	(10.52)	(8.93)
Adverse	0.002	0.005	0.006
	(1.04)	(2.15)	(2.41)
Wound	0.086	0.053	0.041
	(2.26)	(1.50)	(1.09)
Constant	0.131	0.253	0.43
	(6.76)	(12.18)	(20.06)
N	876	876	876
R^2	0.181	0.152	0.265

Note: All models include year dummies. Standard errors are corrected for heteroscedasticity. The numbers in parentheses are t-ratios.

Table 4: Regression Analysis for *Inefficiency-3*

	OLS	*Random Effects*	*Fixed Effects*	
Model	*(1)*	*(2)*	*(3)*	*(4)*
HHI	-0.114	0.011	0.745	-1.522
	(-1.90)	(0.11)	(2.97)	(-2.01)
HHI^2	0.115	-0.021	-0.70	3.942
	(2.19)	(-0.24)	(-3.36)	(2.67)
HHI^3				-2.704
				(-3.17)
HMO	-0.087	-0.201	-0.246	-0.226
	(-0.85)	(-2.24)	(-2.52)	(-2.34)
HMO^2	-0.145	0.030	0.061	0.048
	(-0.65)	(0.23)	(0.47)	(0.37)
Public	0.06	-0.012		
	(5.41)	(-0.78)		
Non-profit	0.078	0.017		
	(8.93)	(1.40)		
Adverse	0.006	0.002	0.002	0.002
	(2.41)	(1.26)	(0.79)	(0.83)
Wound	0.041	-0.008	-0.012	-0.011
	(1.09)	(-0.43)	(-0.60)	(-0.58)
Constant	0.430	0.485	0.376	0.640
	(20.06)	(19.66)	(7.26)	(6.54)
N	876	876	876	876
R^2	0.265	-	0.487	0.494

Note: All models include time dummies. The numbers in parentheses are t-ratios.

Figure 1: Marginal Impacts of Market Concentration on Inefficiency

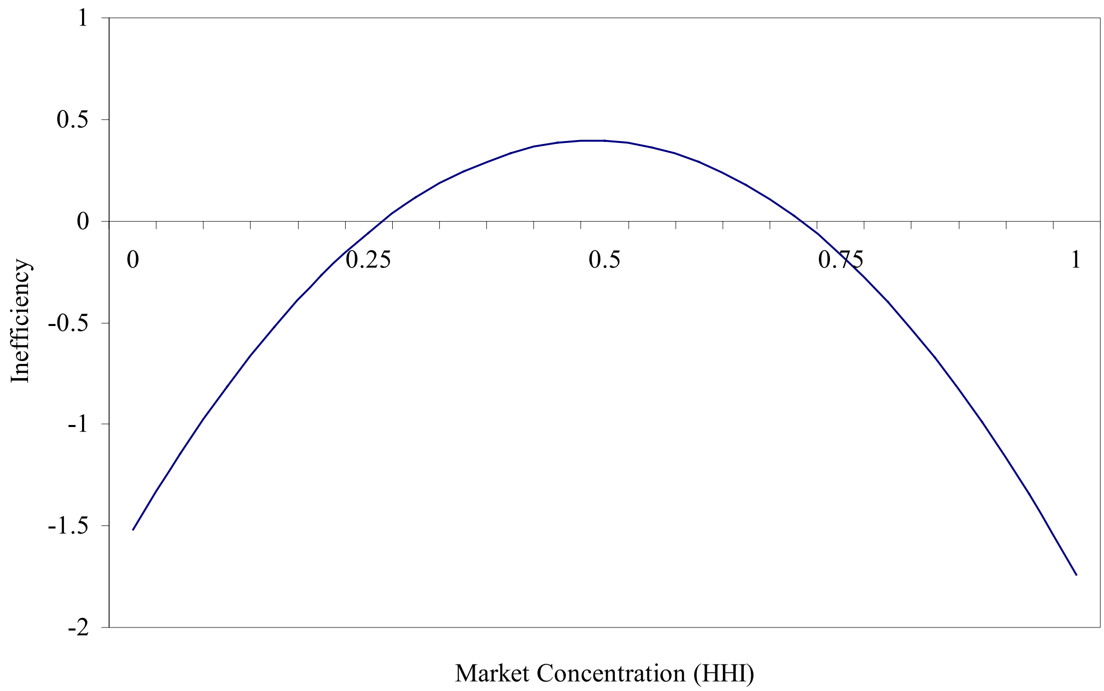

Table A1: Cost Function Estimations

Model	*(1)*		*(2)*	
	Coefficient	*t-ratio*	*Coefficient*	*t-ratio*
Admission	0.595	23.482	0.567	19.848
Visit	0.141	10.330	0.134	11.853
Wage	0.276	13.393	0.274	9.274
Medicare	0.087	1.595	0.110	2.056
Medicaid	-0.187	-2.277	-0.117	-1.402
Surgical outpatient	0.625	4.121	0.502	2.968
Surgical inpatient	0.124	2.338	0.113	2.056
Adverse	0.009	2.094	0.010	2.597
Wound	-0.041	-1.071	-0.017	-0.446
Age	-0.001	-0.101	-0.003	-0.504
Baby	-0.198	-0.561	-0.316	-0.717
Age65	-0.087	-0.341	0.096	0.316
Died	-0.498	-1.087	-0.406	-0.900
NDX	0.001	0.099	0.002	0.291
Female	-0.061	-0.342	0.071	0.364
CMI	0.404	6.938	0.388	6.520
Log (size)	0.214	9.375	0.198	7.413
Income per capita	-0.1E-4	-2.810	-0.1E-4	-2.382
Unemployment	0.001	0.267	0.004	0.833
Bed1000	0.011	14.979	0.014	7.205
Emergency	-0.1E-4	-0.167	-0.5E-5	-0.094
Log (population)	0.069	6.060	0.076	4.425
Time	0.089	5.174	0.084	6.153
Time2	-0.007	-3.381	-0.006	-3.854
Urban	-		0.035	1.053
Teaching	-		0.035	0.927
Constant	5.179	17.297	5.684	14.126
σ_u^2	0.055		0.023	
σ_v^2	0.015		0.012	
N	876		876	

Acknowledgements

I acknowledge the support from the Centers for Medicare and Medicaid Services under Grant No. 30-P-30246/1-01, and the data support from the VA Management Science Group. I would also like to thank Harvey Averch, Kathleen Carey, Roberto Cavazos, Randall P. Ellis, Kevin Lang, Stephen Martin, Thomas G. McGuire, Fred Newman, participants at the 77th Western Economic Association International Conference, and the anonymous referee for their helpful discussions and comments.

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